# A Machine Learning Approach to Predict Properties of Wood Products during Milling

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## Abstract

The wood industry seeks innovative methods to improve process monitoring and adaptive control by modeling workpiece characteristics. This study proposes a sensor fusion approach that integrates data from airborne sound, cutting forces, power consumption, and acoustic emissions while milling diverse wood-based products. The objective of this research is to accurately predict workpiece attributes, such as the density of the wood products to achieve strength grading and the roughness of the machined surfaces to identify tool wear or unsuitable process parameters. To accomplish this objective, machine learning regression was employed by training a model on the predictors chosen through supervised univariate feature ranking. Individual linear regression models per workpiece type depended heavily on the material, where the validation $R^2$ values ranged from 0.1 to 0.99, due to presplitting in the case of samples machined across the fiber and porosity in the case of particleboard samples. A validation $R^2$ of 0.99 could be achieved for the collective modeling of density based on all the collected samples, with samples machined against the fiber being excluded. Surface roughness could be predicted with a validation $R^2$ of 0.91 by excluding samples machined across the fiber and particleboards.


The wood industry has long been interested in monitoring machining processes. However, creating a comprehensive monitoring system that covers all aspects of wood machining is challenging for several reasons (Marchal et al. 2009). The complex nature of wood as a natural material, characterized by features such as knots and different fiber angles, makes it difficult to determine optimal parameters for wood machining (Möhring et al. 2019). The effect of wood fiber angles on the machining process is a prime example of this phenomenon (Gottlöber 2004). When machining solid wood along the fibers, the resulting surface quality is vastly different from machining solid wood across the fibers (Csanády and Magoss 2013a). Furthermore, machining wood across the fibers can increase tool wear rates (Csanády and Magoss 2013b).

Wood machining monitoring has been investigated in many studies by using a variety of sensors (Lemaster et al. 1985, Cyra et al. 1998, Aguilera and Martin 2001, Denaud et al. 2011, Dvoracek et al. 2022). For example, acoustic emission (AE) sensors, with a resonant frequency of 175 kHz, were used for tool wear monitoring during wood machining. Another study used ultrasonic AE to examine the use of carbide-tipped tools and sawblades (Lemaster and Schultz 2016). A novel application of feed-forward neural networks was used to examine the relationship between tool health and airborne sound (AS) from 20 Hz to 20 kHz (Zafar et al. 2015). That study found that the results depended on the wood species, where the tool health classification accuracy was 78 percent when machining softwood and 97 percent when machining hardwood. Another application with AS can be found in Zhu et al. (2002), where tool wear was investigated with a microphone that measured AS up to 100 kHz. The analysis was based on the ratio of AS energy between consecutive teeth.

Additionally, surface roughness has been investigated in many studies. For example, the effect of the tool geometry

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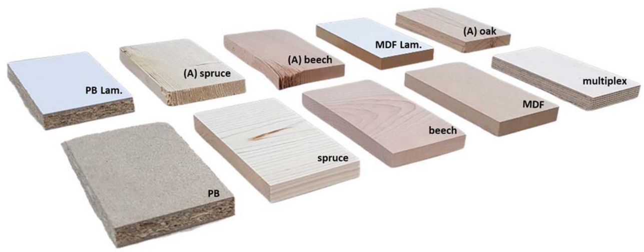


*Figure 1.—Tested workpiece types after machining.*

on AS and surface roughness was investigated by Cyra et al. (1998), with a focus on the relationship between the helical angle of drill bits and AS (4–100 kHz) generated during wood drilling. The surface roughness was modelled with the AS event count, where a Pearson correlation coefficient between 0.76 and 0.99 was found. Another AS feature that can be used for surface roughness prediction is the sound pressure level (SPL). By measuring the sound of wood milling with two microphones, Iskra and Tanaka (2005b) obtained a Pearson correlation coefficient of 0.98 when modeling surface roughness with SPL.

Aguilera et al. (2006) discussed the correlation between AE and surface roughness while milling solid wood. The polynomial fit had an $R^2$ value of 0.59 for a milling head with two knives, whereas a milling head with four knives had a slightly higher $R^2$ at 0.66. Further studies that discuss AE as a means to monitor production processes in the wood industry include Aguilera (2010), Aguilera and Barros (2010), and Murase et al. (2008).

The potential of multisensor systems to further improve process monitoring during wood machining has been investigated by several studies (Aguilera and Barros 2011, Möhring et al. 2019, Nasir et al. 2019). Handling data from multiple sources also requires tailored analysis techniques, which may include the usage of dimensionality reduction and artificial intelligence. For example, the D9203B AE sensor, with a sensitivity from 100 to 1,000 kHz, was used together with other sensors to monitor sawing processes (Nasir et al. 2021). Then, an artificial neural network was trained using fuzzy logic to select features and predict the process quality. Aguilera et al. (2016) also studied a multisensor system to monitor wood milling processes. The loudness of AS was found to correlate with the feed speed and dimensions of the machined chips. Electric current was also studied—it was investigated as a response to be predicted when the chip thickness and the feed speed were taken as predictors. Finally, a training accuracy of 96.6 percent to differentiate between machined materials was achieved by employing machine learning classification with the purpose of autonomous control of the machining process (Eschelbacher et al. 2019).

The usage of a new AS microphone, based on laser interferometers (Fischer 2016), to study wood machining was explored by Derbas et al. (2021, 2023). In these studies, it was shown that wood milling processes can be monitored by using the sound of singular cuts, which were segmented from the measured signals.

The present research aimed to predict the density and surface roughness of milled wood products using signals acquired during milling such as cutting forces, AE, AS, and power consumption. To achieve this, five distinct wood-based materials and five different solid wood samples were investigated. Each material was tested at one cutting speed. From the measured signals, features were calculated and chosen for the regression task through the application of univariate feature ranking. The regression task was then divided into two separate categories: linear models for individual materials and regression trees for all materials collectively.

*Table 1.—Summary of workpiece types and properties.*

| Material[a] | Density ($kg/m^3$) | Surface roughness, $R_z$ (μm) |
|---|---|---|
| (A) Beech (*Fagus sylvatica*) | 640 ± 10 | 87 ± 40 |
| (A) Oak (*Quercus rabor*) | 591 ± 78 | 196 ± 109 |
| (A) Spruce (*Picea abies*) | 431 ± 11 | 161 ± 98 |
| Beech (*Fagus sylvatica)* | 646 ± 5 | 74 ± 12 |
| Spruce (*Picea abies*) | 365 ± 23 | 22 ± 6 |
| Multiplex | 603 ± 18 | 37 ± 5 |
| PB | 618 ± 10 | 197 ± 299 |
| PB lam. | 584 ± 6 | 73 ± 21 |
| MDF | 634 ± 6 | 77 ± 14 |
| MDF lam. | 640 ± 7 | 67 ± 10 |

[a] A = samples machined across the fiber; PB = particleboard; lam. = laminated samples; MDF = medium density fiberboard.

## Materials and Methods

### Samples and process components

The current study focused on the machining of engineered wood products and solid wood (Fig. 1). The samples were cut to have a length of 100 mm, a width of 200 mm, and a thickness of 30 mm.

Ten different types of workpieces were used in the present study (Table 1). The density of each sample was calculated by measuring the weight with a precision scale and dimensions with a measuring tape. The Alicona Infinite Focus G5 digital microscope from Bruker Alicona Imaging GmbH (Raaba, Austria) was used to measure the surface roughness, $R_z$, taken as the average peak-to-valley height of the profile (Deutsches Institut für Normung Normenausschuss Technische Grundlagen 2009) at three locations (start, middle, end) on the machined side of each sample with a scanned length of 12.5 mm. These measurements were used as responses to be predicted by using the signal features from the sensor signals.

The machining was executed on a MAKA PE 170 5-axis CNC machine (Fig. 2) from MAKA Systems GmbH (Nersingen, Germany). The milling head from Leitz GmbH & Co. KG (Oberkochen, Germany) had a diameter of 125 mm and a rake angle of 15°. It was equipped with one cutting edge (wedge angle of 55°, giving a clearance angle of 20°) on one side and a counterweight on the other. The cutting speed was

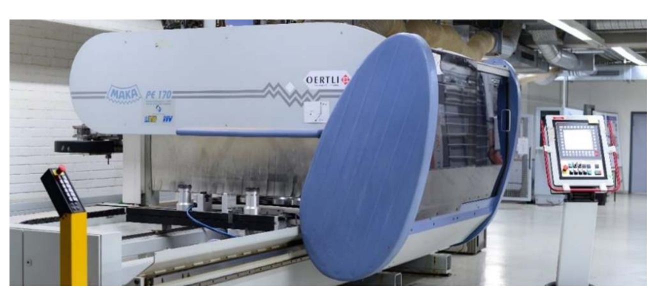


*Figure 2.—MAKA PE 170 CNC.*

Table 2.—Measurement types and sensors.

| Sensor | Producer | Measurand | Sampling |
|---|---|---|---|
| ETA 250 Ultra | XARION GmbH (Vienna, Austria) | Airborne sound 10 Hz to 1 MHz | 2 MHz |
| QWT-MCX | QASS GmbH (Wetter, Germany) | Structure-borne sound 5 Hz to 1 MHz | 1.6 MHz |
| Dynamometer type 9272 | Kistler Group (Winterthur, Switzerland) | Cutting forces in three axes | 1 kHz |
| WT330 power meter | Yokogawa Electric Corporation (Tokyo, Japan) | Power consumption | 10 Hz |

set to 60 m/s, with a feed speed of 11 m/min and a rotational speed of 8,982 rotations per minute (rpm). The cutting depth was set at 5 mm, which gave an average chip thickness of 0.24 mm and a feed per tooth of 1.23 mm per tooth.

Each experiment was repeated five times using a randomized design, resulting in a total of 50 runs. Additionally, the properties of the machined samples were measured at the start, midpoint, and end of the machined length, yielding a data set of 150 records.

## Sensors and acquisition

The machining process was monitored by a total of four sensors (Table 2).

The AE sensor was attached to the sample holder (Fig. 3b). The ETA 250 Ultra was attached with a sensor arm to the spindle housing and placed at a distance of 100 mm from the cutting tool (Fig. 3a). AE and AS signals were recorded with the HFIM Optimizer 4D acquisition system from QASS GmbH (Wetter, Germany). The sampling frequency was set to 1.6 MHz for AE and to 2 MHz for AS.

The cutting forces, determined by a type 9272 dynamometer (Fig. 3c) and amplified by three type 5015A charge amplifiers (Winterthur, Switzerland), were measured at the sample holder and recorded in axial, lateral, and normal directions. The sampling frequency for all three forces was set to 1 kHz, and the acquisition was done by a BNC 2110 data acquisition card and the LabVIEW software from National Instruments (Austin, Texas).

The WT330 power meter (Fig. 3d) was used to measure the power consumption of the machining process. These measurements were done directly on the motor of the spindle and imported to a laptop through a universal serial bus (USB) port.

## Machine learning

Feature selection was done by supervised univariate feature ranking to ensure that only relevant predictors were used for training the model, as including irrelevant predictors could be detrimental to the training of the models. For regression problems, this could be done by calculating the importance score (Eq. 1) based on the $p$ value of an $F$ test. In MATLAB, this is implemented in the fsrftest function. A threshold was defined at a confidence level of 5 percent. Important predictors were associated with a $p$ value below 0.05 and therefore a higher importance score. On the other hand, irrelevant predictors will have a low importance score and a higher $p$ value (Kuhn and Johnson 2019).

$$Importance = -\log(p) \tag{1}$$

Individual models for each material were based on linear models and were trained by the fitrlinear MATLAB function. For collective modelling, regression tree models were used by

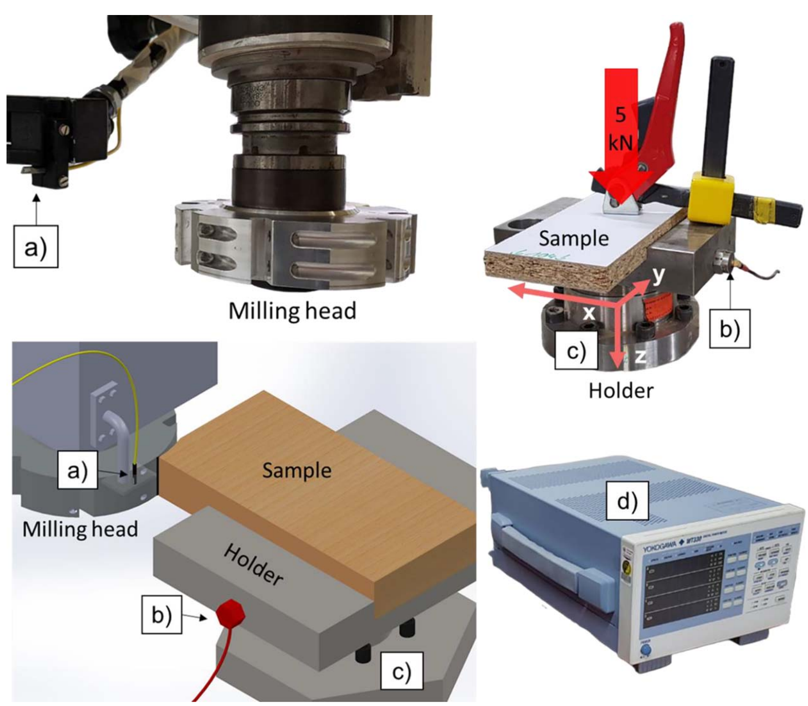


Figure 3.—Experiment setup with (a) ETA 250 Ultra, (b) QWT-MCX acoustic emission (AE) sensor, (c) Dynamometer type 9272, and (d) WT330 digital power meter.

Table 3.—List of default hyperparameters in the MATLAB environment.

| Model | Hyperparameter | Description | Default |
|---|---|---|---|
| Regression tree model | MinLeafSize | Minimum number of observations per tree leaf | 1 |
| fitrtree | MaxNumSplits | Maximum number of splits for the decision tree | all |
| | NumVariablesToSample | Number of predictors to select for each split | all |
| Linear model | Lambda | Regularization term | log-scaled |
| fitrlinear | Learner | Type of learner | svm |
| | Regularization | Regularization technique | rigde |

means of the MATLAB fitrtree function. In both cases, the default hyperparameter values were used (Table 3).

All models were validated using *k*-fold cross-validation with five folds. For each fold, a model was trained and tested on different subsets of the design matrix to include all the records in the data set (Fig. 4). Finally, the predictions were concatenated and used to calculate the fit and error metrics. For the linear models, this amounted to 12 records for training and three records for validation of each fold. The regression tree approach on the other hand was trained on 120 records and validated on 30 records for each fold. A special case for the partitioning was specified in the case of the regression trees, where the 30 records for validations were uniformly selected from all workpiece types, giving three records for each workpiece type. This ensured that none of the ten different workpiece types was under- or overrepresented in the model training and validation.

## Results and Discussion

### Signal preprocessing

All signals were imported into the MATLAB environment. The goal was to identify regions of interest in the signals and to calculate features that could act as predictors for the measured responses, which in this case would be the density of the machined sample and the resulting surface roughness.

For AE and AS (Fig. 5), the signals had a very high temporal resolution and therefore could be segmented into individual cuts, as was done in Derbas et al. (2023). The cut detection method was based on peak detection and set optimization. From these cuts, signal features were calculated, grouped, and averaged. In this case, the root mean square (RMS) was chosen as a loudness parameter, and the mean frequency, calculated with the meanfreq MATLAB function, was chosen as a frequency representation.

Similarly, the power data (Fig. 6) were split into three portions to represent the start, middle, and end of the machined length of the samples. The power consumption was calculated by multiplying the measured voltage by the current.

Cutting forces (Fig. 7) were acquired for three directions, and the RMS feature was taken to represent the intensity of the forces.

### Regression analyses

*Surface roughness,* $R_z$.—After feature selection for each material, the training of individual models showed that the outliers for Sample Sets A and PB were causing significant problems in the training and validation of the models. Otherwise, the models for the other materials had a good fit (Fig. 8), with $R^2$ values ranging from 0.84 to 0.95. The most important feature in this case was observed to be the AS loudness feature (RMS).

All materials in the regression tree led to poor fitting and feature importance results (Fig. 9). This can be attributed to the measurements on the A and PB samples, due to the bad surface finish and the porous surface, respectively. Three variables did not meet the feature importance threshold, while those that did only slightly surpassed the set value at a confidence level of 5 percent. The validation $R^2$ was 0.17, and the root mean square error (RMSE) was 139.4 μm. The model also underestimated the actual values, since the majority of the least square lines fell under the perfect fit. This can be attributed to the outliers from the PB samples.

After excluding the records that were attributed to the A and PB samples, the feature selection and the regression fit improved significantly (Fig. 10), where all but one variable had a significant importance score. Material type and the cutting forces were the predictors with the highest importance

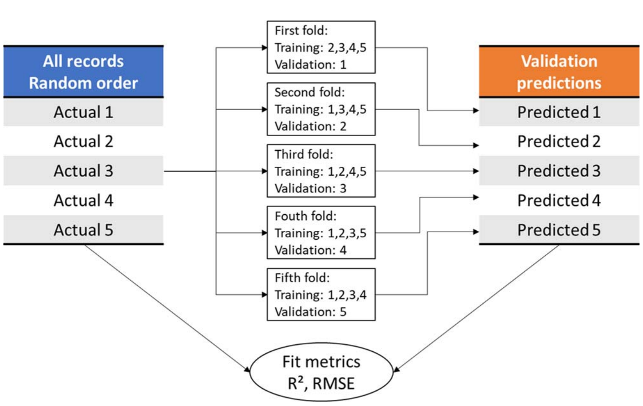


Figure 4.—k-fold cross-validation process.

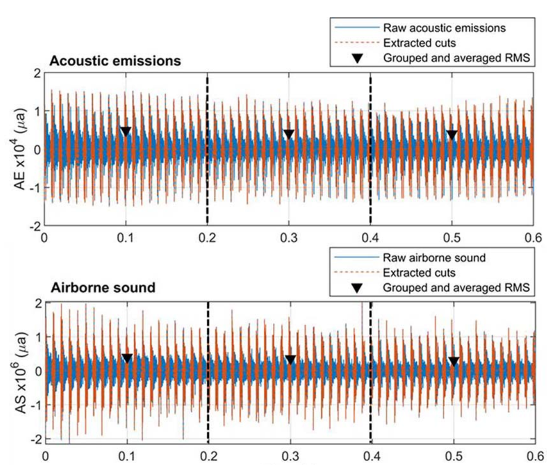


Figure 5.—Exemplified acoustic emission (AE; top) and airborne sound (AS; bottom) measurements for a spruce sample and the calculated RMS values.

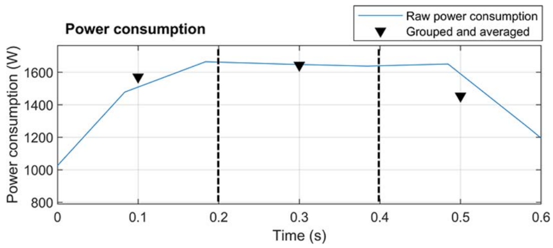


*Figure 6.—Exemplified power consumption for a spruce sample.*

scores. The fit improved to a validation $R^2$ value of 0.91 and RMSE of 9.9 μm. Some clusters could be readily identified, such as the clusters of the spruce and multiplex samples, as opposed to the other clusters, which included beech and medium-density fiberboard (MDF) samples. While the individual models achieved lower $R^2$ values than the collective model ($p < 0.05$), the RMSE was seen to be lower for the individual models as well ($p < 0.05$). As there was a need to exclude samples of a specific wood product during the collective modelling, it would be better to use individual regression models to identify the limitations that arise when measuring accurate values for surface roughness in the case of A and PB materials. Predicted surface roughness can be used as a sign of increased tool wear or unsuitable process parameters, enabling early reaction to avoid elongated downtime due to tool failure.

The monitoring of wood machining to predict surface roughness can be found in the current literature. For example, SPL was used to monitor the process of machining MDF boards to predict surface roughness $R_z$. The fitting on a total of four data points per variation led to $R^2$ values between 0.73 and 0.94 (Aguilera and Barros 2011). As a comparison, the current study had 15 records per variation and an $R^2$ of 0.89 (RMSE = 8 μm) for MDF and an $R^2$ of 0.94 (RMSE = 4 μm) for laminated MDF in validation. Similarly, a study by Iskra and Hernández (2010) evaluated the monitoring of the machining of hardwood along the fiber (white birch, *Betula papyrifera* Marsh.) with a microphone to predict the surface roughness $R_z$. The results showed an $R^2$ of 0.81 and an RMSE of 3.04 μm. Analogously, the current study found similar results for beech samples machined along the fiber, with an $R^2$ value of 0.89 and a higher RMSE at 8 μm. Finally, the relationship between AS RMS and surface roughness $R_z$ can be clearly seen in Figure 11.

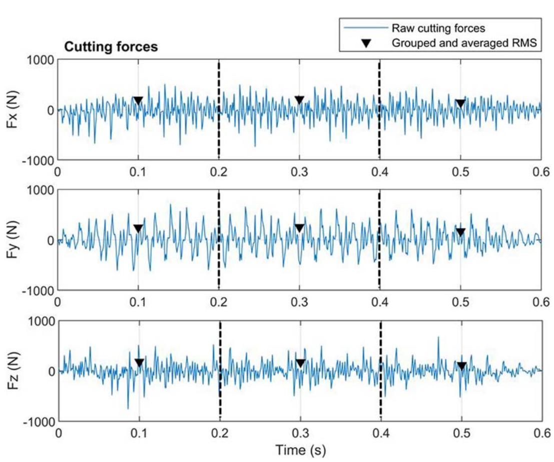


*Figure 7.—Exemplified cutting forces RMS for a spruce sample in all three directions.*

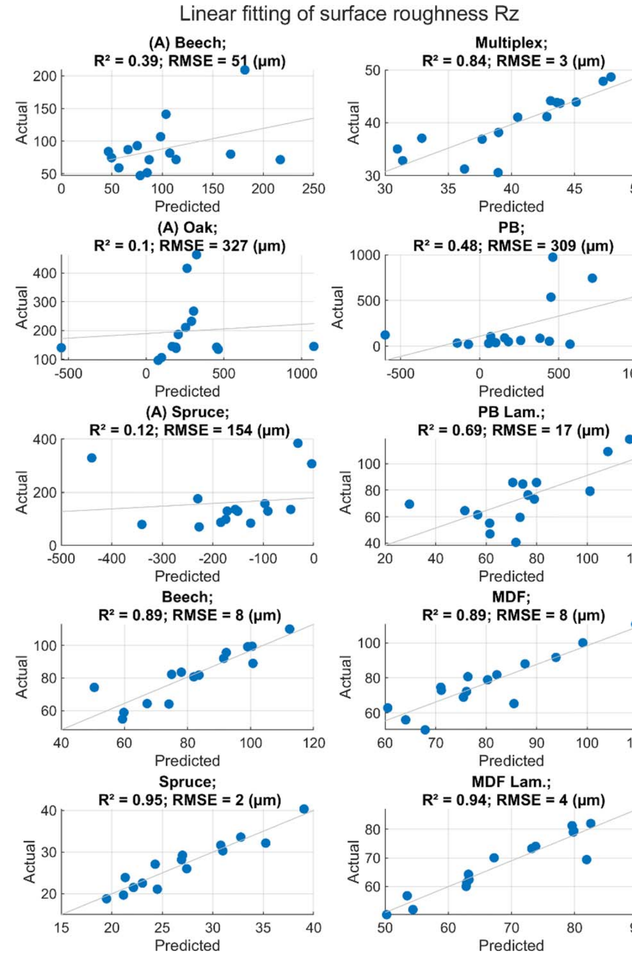


*Figure 8.—Actual versus predicted linear models for the prediction of surface roughness ($R_z$) in validation.*

This correlation was observed by many other authors (Iskra and Tanaka 2005a; Aguilera 2009, 2010; Iskra and Hernández 2009, 2010; Aguilera and Barros 2010, 2011) in the current literature and could be refined in the current study, as this correlation was established for more materials in the same experimental design.

*Density.*—Individual linear models to predict the density of the machined samples, after feature selection for each material, showed a good fit for all materials except for the samples machined across the fiber (Sample Set A). This can be attributed to the sporadic presplitting during machining, which significantly influenced the raw data. An example of the linear fitting to predict the density of the machined samples can be seen in Figure 12. Power consumption and cutting forces were observed to be the most important variables.

The feature ranking showed that material type was the most important predictor (Fig. 13), followed by the mean frequency of AE and power consumption. As opposed to including all materials for the prediction of surface roughness, including all materials for predicting density did not affect the $R^2$ fit metric ($R^2$ around 0.95). On the other hand, the data points associated with Sample Set A caused high error, with an RMSE of 28.9 kg/m$^3$.

Excluding Sample Set A from the models improved the $R^2$ value from 0.95 to 0.99 and reduced the RMSE error from 28.9 kg/m$^3$ to 11.1 kg/m$^3$ (Fig. 14).

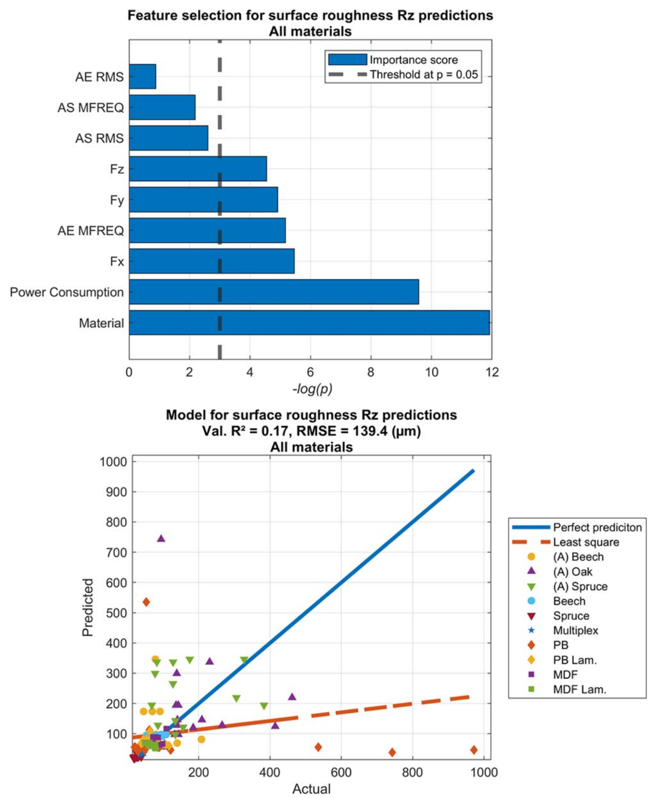


*Figure 9.—Feature importance plot (top) and validation predictions versus actual values for surface roughness, all materials.*

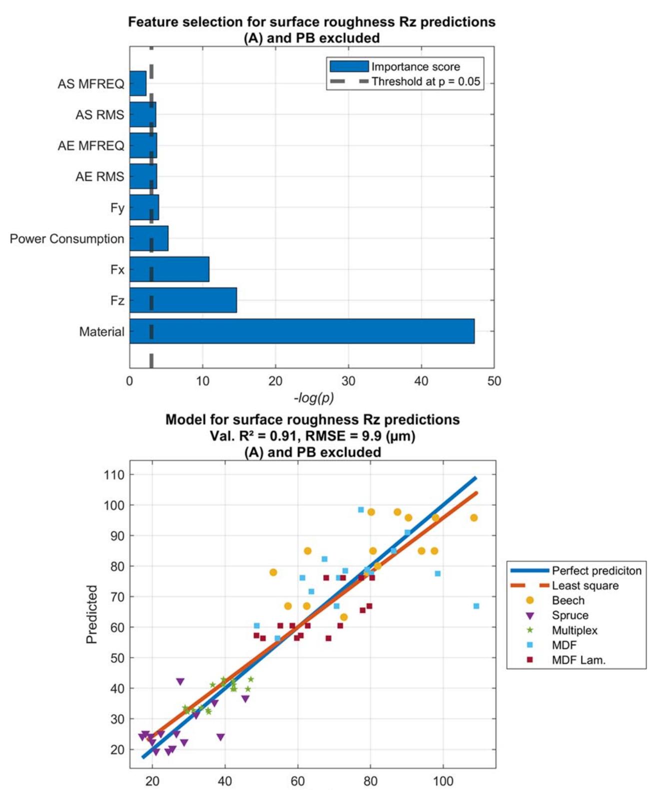


*Figure 10.—Feature importance plot (top) and validation predictions versus actual values for surface roughness with Samples Sets A and PB excluded.*

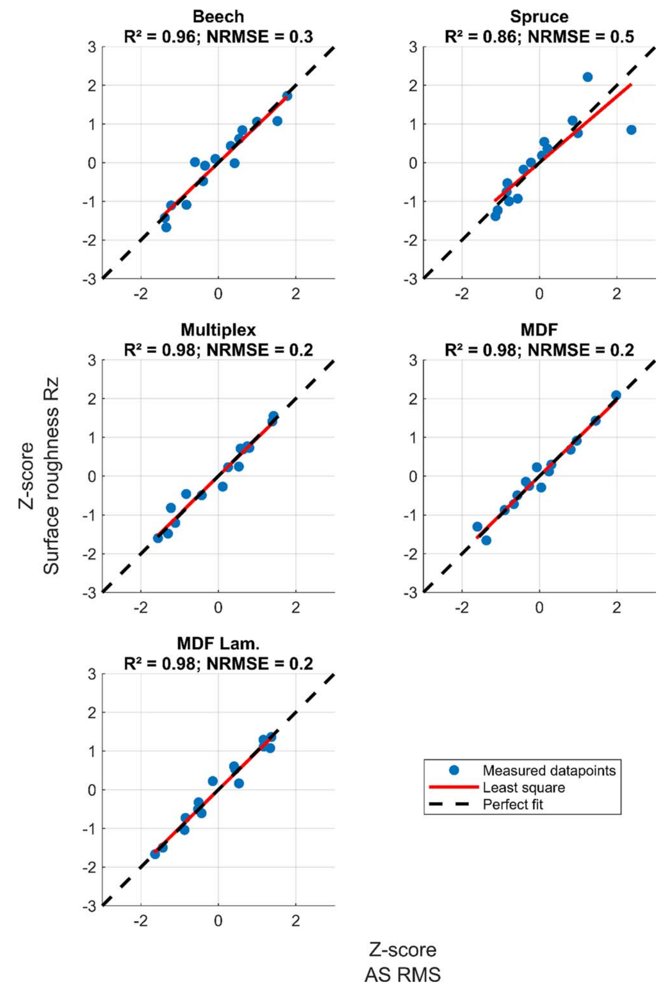


*Figure 11.—Correlation between surface roughness* $R_z$ *and airborne sound (AS) RMS.*

Comparison of the collective and individual modelling of the density revealed that while the $R^2$ value was higher for all materials in the collective model ($p < 0.05$), the corresponding RMSE was also higher ($p < 0.05$). This can be attributed to an ecological fallacy, where predictions across groups might lead to the exaggeration of the goodness of fit while also increasing the error for all individual groups (Lubinski and Humphreys 1996). Therefore, using linear regression for modelling the density would be preferred, as the collective modelling primarily captured the variance found between the different categorical wood products. No other study could be found that focused on the prediction of the machined sample density. The application of such a predictive model in manufacturing processes can enable, e.g., strength grading, as the mechanical performance of wood is highly correlated with density (Shelly 2001).

## Conclusion

In conclusion, the current study aimed at enhancing process monitoring and adaptive control in the case of wood milling by proposing a sensor fusion approach. Ten different types of workpieces were tested, including five engineered wood products and five solid wood samples with different species and cutting directions. Data from acoustic emissions, airborne sound, cutting forces, and power consumption were integrated

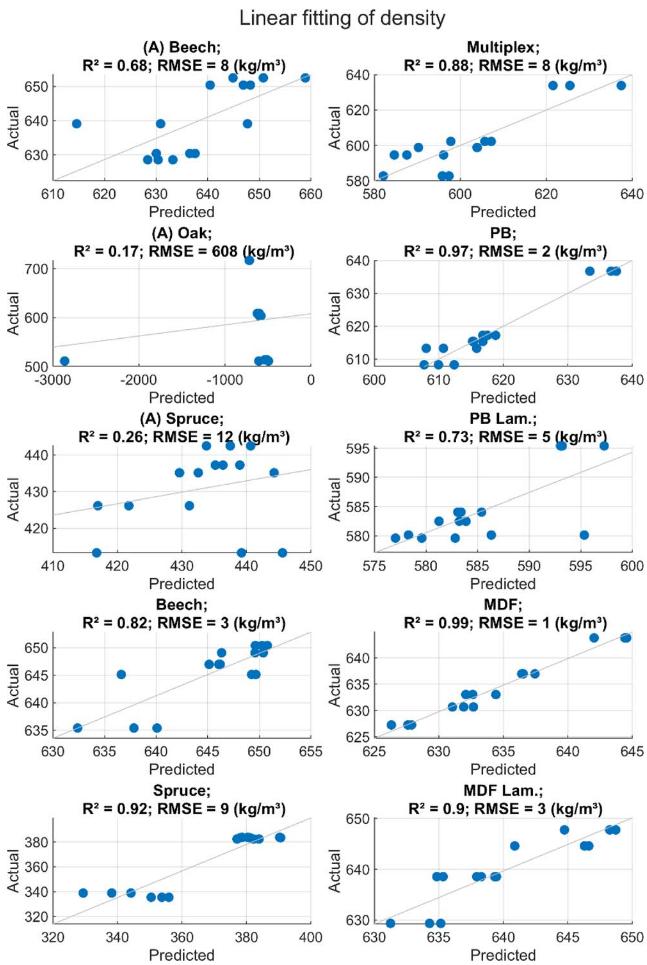


*Figure 12.—Actual versus predicted linear models for the prediction of machined sample density in validation.*

during milling to accurately predict workpiece attributes such as density and surface roughness. Next, data were preprocessed, the most important features were selected, and machine learning regression was applied. The models exhibited varying performance, with validation $R^2$ values ranging from 0.1 to 0.99. Notably, a validation $R^2$ of 0.99 was achieved for collective density modeling, excluding samples machined against the fiber. Surface roughness prediction yielded a validation $R^2$ of 0.91, excluding samples machined across the fiber and particleboards. Individual linear models for each material made it easier to identify the outliers that caused difficulties in training the models for samples machined across the fiber and particleboards. It is important to acknowledge the inherent complexity in modeling across various materials as well, where surface roughness measurements on particleboards and samples machined across the fiber led to data that could not be modelled together with data from other samples. Similarly, a collective model to predict the density of the machined samples would have a high error due to the significant density differences across wood species and engineered wood products.

Application of these types of models in the industry will add insight into the current status of the machining process as well as the expected quality of the manufactured products. To do so, models need to be adapted to work with new data and to continuously learn from monitored processes.

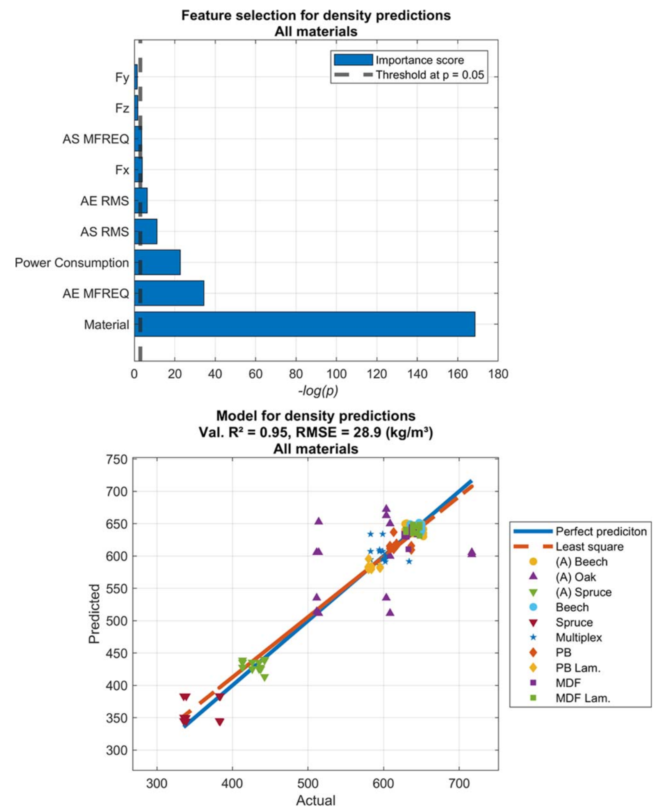


*Figure 13.—Feature importance plot (top) and validation predictions versus actual values for density, all materials.*

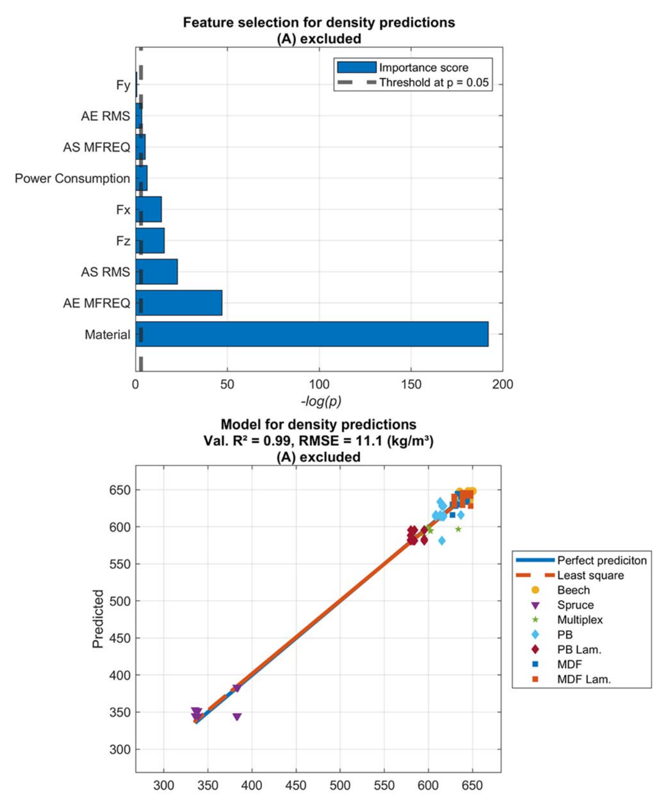


*Figure 14.—Feature importance plot (top) and validation predictions versus actual values for density with Sample Set A excluded.*

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## Declaration

The authors declare no conflict of interest.

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